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Title: Data organization in laser-based powder bed fusion for metals

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Abstract

Data analytics (DA) and artificial intelligence (AI) have been chosen as the technologies for extracting new knowledge and making better decisions in additive manufacturing (AM) processes. They have been chosen because accurate and complete physics-based, process-simulation or mathematical models do not exist. DA and AI models should be based on measurable data collected by part and process sensors. This paper is focused on how to organize the data collected from such sensors. An example is also provided to show how to store AM-related data in a hierarchical data structure that is consistent with the data from multiple sensors. The data provides functions and properties at various stages in a product lifecycle. The associated metadata for both functions and properties are organized in the same hierarchical structure according to the relationships of machine, build, melting laser beams, process planning, in-situ monitoring, ex-situ inspection, material microstructure imaging, and mechanical testing. Sample data with metadata are stored in a file in the format of Hierarchical Data Format 5 (HDF5). The paper provides an organization of complex AM data that can support AM software tools for a variety of product lifecycle activities.

***Keywords**:* Additive Manufacturing; Data Organization, Meta Data; Senor Data; In-process Data; Ex-situ Inspection Data

1. Introduction

A report on additive manufacturing (AM) measurement-science needs [1] supported the notion that controlling AM processes requires an integrated suite of data analytics (DA), artificial intelligence (AI), and physics-based simulation-based software tools [2, 3]. For instance, there is a software tool that uses sensor data and models to make predictions about the stabilities and variations in laser-based powder bed fusion of metals (PBF-LB/M). Addressing these needs [4] is necessary for AM technology users to ensure that they can fulfill quality requirements based on data. These needs are based on the PBF-LB/M process [5]. Data organization capabilities [6] have been identified to improve the ability to meet those requirements. Requirements include (1) defect characterization and rectification [7-9], (2) laser-powder interactions and material transformation during the build [3], (3) the knowledge of microstructure evolution during the melt-pool cooling process [10], and (4) the prediction of mechanical properties of fabricated parts [11].

Characterizing defects, such as pores, cracks, unmelted powders, soot, dimensional inaccuracies, poor surface finish, and deleterious microstructures is difficult because of the inconsistencies in the PBF/LB-M process. These inconsistencies are due to variations in the material properties, the process parameters, and the build environment [12]. Research efforts to understand their impacts focus on (1) discovering the process-structure-property (PSP) relationships and (2) using those relationships to improve the process control for the consistent part quality [13]. Successful implementation of these tasks needs data, which relies on a variety of in-situ and ex-situ measurement devices such as imaging sensors, thermal sensors, video cameras, acoustic sensors, ultrasonic sensors, vibration sensors, and X-ray Computed Tomography (XCT). Important features of the dataset can be characterized as 4Vs: volume, variety, velocity, and veracity [14]. Handling and analyzing these 4V data can help identify the instabilities and inconsistencies that occur during the PBF processes.

A significant amount of experimental research has been directed towards using 4V to understand the Process-Structure-Property relationships and to use them to optimize the process parameters [15, 16]. Other research studies have also focused on physics-based, numerical models to predict the properties of the manufactured parts and to prevent defects from occurring [17]. Both experimental and numerical efforts have laid a good foundation for enhancing the understanding of the process; however, they are costly and time consuming. Therefore, there is a need for developing a multi-sensor, monitoring strategy to collect data and analyze data in real time. These data will be organized and used as inputs to a machine learning algorithm that allows users to understand and predict the PSP relationships for every new material.

Before using machine learning, a systematic organization of data is needed. The benefits of organization are associated with the FAIR principles for data management and stewardship [18]. FAIR stands for (1) Finding data with unambiguous identifiers, (2) Accessing that data with defined protocols, (3) Interoperability to support shared terminology, and (4) Reusing existing data in new applications. For the AM technology, the FAIR principles can improve data registration, defect tracing, and simulation validation.

In this paper, the “data”, which is collected by several different types of Laser-based Powder Bed Fusion of Metals (PBF-LB/M) sensor data, include images [19]. The traditional, relational database structure or the eXtensible Markup

Language (XML) structure do not fully support AM image data. Hierarchical data formats use attributes to save metadata, which requires an additional validation mechanism for data curation [20]. HDF5 (Hierarchical Data Format version 5) has “group”, which is like a directory in the computer file structure, for storing related images [21]. A group can have one or more subgroups for organizing different subcategories of data. Each subgroup may have attributes for storing meta data for its datasets. The metadata associated with each dataset provides important information about that dataset. Because of the data structures available in HDF5, we used them to organize AM data in this work.

The main purpose of this paper is, therefore, to provide a feasible method to organize and store AM metadata, images, numbers, tables, and text. Based on this method, this paper describes a HDF5 file structure for storing data from an AM product lifecycle including the design, stock material, the process, the microstructure, and the mechanical property. There are three major contributions of this paper. First, there is a novel data structure to organize AM data - from machine to mechanical property - as input to DA and AI software applications. Second, there is metadata in tables that associate with sensor, instrument, machine, images, and tests necessary for data analytics. Third, there is an implementation of that data structure using HDF5 format.

This paper has six sections. Section 2 reviews related publications in AM data organization and file structures. Section 3 describes a general hierarchical data model to handle big data from a variety of sensors commonly used in PBF-LB/M process monitoring and microstructure/structure inspections. This section also describes an implementation with metadata elements and sensor data in HDF5 as an example to store the data. Section 4 discusses the proposed procedure. Section 5 concludes the paper and identifies the future work.

2. Review of data and meta data

To develop a file structure for storing different types of AM sensor data, we first need to understand their current uses in in-situ monitoring, ex-situ inspection, and part prediction. This section provides a review of the different types of sensors, including their characteristics, categorization, and uses from the open literature. In data organization, the section describes structures in available databases including Additive Manufacturing Material Database* (AMMD), Material Data Curation System† (MDCS), and Common Data Dictionary (CDD). Two major issues associated with that data: organization in a file and pilot implementation. The section discusses the technical barriers and the needs for research and development.

Several different types of sensors have been designed for in-process monitoring and post-process, nondestructive inspections. Co-axial and off-axis cameras collect images that are used for in-situ monitoring. Co-axial cameras capture images of the melt-pool. The different images are used to measure melt-pool dimensions over a specified time period. Other coaxial sensors, such as (1) pyrometer and photodiode, can provide discrete, point-wise measurements and (2) spectrometer can be used to analyze energy peaks and spatters [22]. Off-axis sensors, such as Digital Single Lens Reflex (DSLR) cameras are used to take images of the powder bed each time it is recoated. A combination of flashlights from different illuminations can detect anomalies on each scanned layer [23].

High-speed cameras can record the melt-pool creation process including melting and solidification. In addition, the size, shape, count, and cooling rate of spatter particles can be measured using a combination of infrared pyrometer and high-speed infrared thermography [24, 25]. In post-process inspection, X-ray Computed Tomography (XCT) instruments are commonly used to quantify internal defects, e.g., to identify locations and size distribution of the pores, which form in several ways, e.g., lack-of-fusion pores, gas pores, keyhole-induced pores, and near-surface pores [26]. These two types of sensors record the AM processing history, which is used to discover the processing-microstructure relationships and the root-cause of the variation of the material performance.

Once parts are fabricated, conventional techniques including SEM, Electron Backscattering Diffraction (EBSD) microscopy, Energy Dispersive Spectroscopy (EDS) are used to study the location- specific, microstructural features. These features include microstructural segregations, morphology, and texture [27]. Zitelli et al. [28] described the microstructures and process-related defects in 3D printed stainless-steel parts. Optical micrographs show distinct grain sizes, crystal orientations, and shapes in different laser scanning directions. These microstructure features are related to different laser scanning strategies. Another work by Pham et al. [29] investigated the role of side branching during grain growth in the solidification process. The direction and length in side-branching play an important role in determining the grain shape and size.

To accommodate these different and complex datasets, the Additive Manufacturing Materials Database (AMMD) defines data schemas and meaningful relationships for users to query the database [30]. The schemas include data models for material, process, and post-process properties. Several unique types are also designed to represent metadata about sensors. AMMD is developed based on the Material Data Curation System (MDCS) with specific AM build data as an extension [31]. MDCS is another NIST database, which provides a means for capturing, sharing, and transforming unstructured data into a structured format based on the Extensible Markup Language (XML) [32]. XML is extensible for future development and transformable for other specific applications. The Common Data Dictionary (CDD) [33] is a working item on standardizing terminology and concepts for PBF-LB/M AM. CDD can be used to organize AM data in file structure or database schema.

There are two gaps in the preceding review. The first gap is that images from photogrammetry or thermometry and signals from pyrometry are not well suited for using XML. XML is

* https://ammd.nist.gov
† https://mdcs.nist.gov

primarily for organizing textual data. The second gap is in handling a large quantity of image and graphical data. XML is not designed to handle such data. We attempt to address these gaps in this paper.

3. A hierarchical structure for AM data organization

This section describes the AM file structure based on the HDF5 format. This data model is designed to accommodate the information of the processing-structure-property relationship including metadata for AM machine, build, design, powder material, melting laser beam, part, coaxial camera, staring (layer-wise) camera, X-ray Computed Tomography (XCT) machine, coordinate measuring machine (CMM), surface roughness measuring instrument, optical microscope, scanning electron microscope (SEM), electron backscattering diffraction (EBSD) SEM, powder X-ray diffraction (PXRD), ultrasmall-angle X-ray spectroscopy, energy dispersive spectroscope (EDS), and mechanical property test machine. The use of this data model is demonstrated in figures in some of the following subsections. An overview of the data groups and their relationships in an HDF5 file are shown in Fig. 1. It is a hierarchical structure. In this example, the Machine data group can have multiple Build subgroups, labeled as Build-1, Build-2, etc., and each subgroup can have multiple entries for Melting Laser Beam since each laser beam may scan a different part in the same build. The Part group is under the Melting Laser Beam to record the information about the fabricated parts. These subgroups include the data about Part Design, Powder Material, Process-oriented, In-situ Measurement, Ex-situ Measurement, Microstructure, and Mechanical Property Test. They will be described in the following subsections.

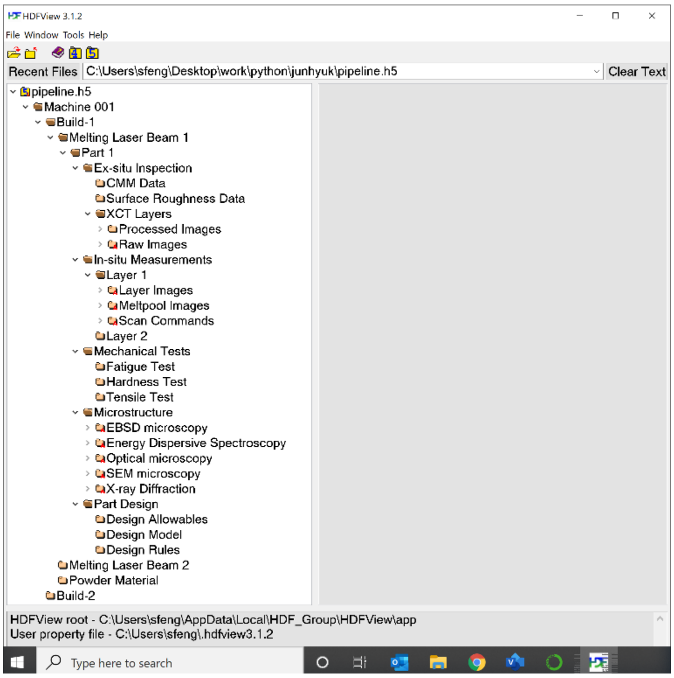

Fig. 1. Data structure overview.

3.1. Machine

The group "Machine" is used to model a laser, powder-bed, fusion machine that fabricates metal parts. The machine data structure comprises many elements; required data elements are shown in Table 1.

Table 1. AM machine data elements.

Data element	Description	Data type
Machine ID	unique identification of the AM machine	String
Manufacturer	name of the manufacturer	String
Machine model	model name and number	String
Machine capability	description of machine capabilities including maximum power, maximum scanning speed, powder spreader type, etc.	String
Size	the maximum build size on the build platform	Unit of Volume
Number of melting laser beams	the total number of melting laser beams in the machine	Integer
Number of builds	the number of builds in a specific period of time	Integer

3.2. Build

Build refers to a process to fabricate metal part(s). The build data structure consists of data elements concerning many aspects of the operation. An overall build data structure in HDF5 can be found in Fig. 1. The required data elements are shown in Table 2.

Table 2. AM build data elements.

Data element	Description	Data type
Build ID	unique identification of an operation to fabricate parts from a bare plate	String
Number of parts	an integer number	Integer
Part model(s)	CAD model name and serial number	CAD Model
Number of melting laser beams	Number laser beams used in the build	Integer
Powder material	Material name, manufacturer, chemical composition	Material type
Date and time	Starting and finish dates and times	Multiple entries of date-time type
Inert gas type	a description (e.g., Nitrogen, Argon)	String
Oxygen level range limit	a percentage (e.g., 0.5%)	Double
Operator ID	Operator identification	String

3.3. Powder material

The powder-material data model includes the size distribution and the physical/chemical/mechanical properties. The details of powder material data elements can be found in many AM material databases (e.g., NIST AMMD) and are thus out of scope of this paper [30].

3.4. Melting laser beam

Melting-laser-beam data model is used to describe the properties of a melting laser beam in a build. Required data elements are shown in Table 3. The entry “fundamental type” means the full description of a measured value. This type includes the value, unit, and uncertainty quantification.

Table 3. Melting laser beam data elements.

Data element	Description	Data type
Beam ID	unique identification of the melting laser beam	String
Contour scan speed		m/s
Contour laser power		W
Infill scan speed		m/s
Infill laser power		W
Infill scan speed		m/s
Infill laser power		W
Upskin scan speed		m/s
Upskin laser power		W
Down skin scan speed		m/s
Down laser power		W
Hatch spacing		mm
Beam diameter		mm
Laser beam coordinate system	The laser beam coordinate system relative to the build platform coordinate system	String

3.5. Process-oriented data

Process-oriented data specified how the part is fabricated layer-by-layer. The data structure consists of data element in many aspects. Required data elements are shown in Table 4.

Table 4. AM process-oriented data elements.

Data element	Description	Data type
Scanning ID	unique identification of a set of laser location control commands	String
Layer number	the powder layer number	Integer
Command time	the time that a position command is sent	t
Scan position	the commanded location of the laser beam (x, y)	mm, mm
Laser power (P)		W

An example of scanning commands in a process-oriented dataset is shown in Fig. 2, which includes the command line number, time stamp, X-location, Y-location, instant laser power, and camera trigger (2 = trigger, 0 = no trigger).

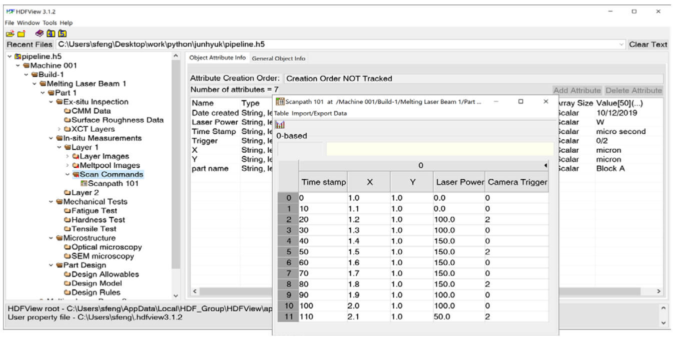

Fig. 2. Laser-scan-command data structure.

3.6. Part

Part describes the design of a metal part. The model can be a Computer-Aided Design (CAD) model. Required data elements are shown in Table 5.

3.7. Coaxial images

Coaxial images are generated from a coaxial camera looking at the melt pool. Required data elements are shown in Table 6. An example of coaxial image of melt pool in the data structure of the HDF5 file can be found in Fig. 3. To record the details of the imaging process, metadata is needed so that the triggering time can be related to the location of the laser. The image files are saved along with the text data to label the recording instance and environment.

Table 5. AM part data elements.

Data element	Description	Data type
Part ID	unique identification of the part	String
Design model	identification of the CAD model	CAD file
Design allowables	restrictions and available design parameters	String
Design rules	rules that a designer needs to follow	String
Setup	Part setup on the build platform in the melting laser beam coordinate system	String

Table 6. Coaxial image data elements.

Data element	Description	Data type
Image Name	the name of the image	String
Image ID	a unique identification number of the image	Integer
Triggering Time	the time when the camera is being triggered to take the picture based on the scanning program in xy2-100	Date-time type
Instant laser power	the laser powder at the time of image taken	W
Frame Rate	frame per second (fps) if it is a movie	Integer
Folder Path	the directory path for locating the folder that this image was saved	
Sensor ID	the identification of the image sensor	String
Sensor	sensor type, purchase data,	String

description	specifications, lens distortion information, etc.		
Sensor installation	installed date, installer		
Sensor configuration ID	Sensor configuration description must have the following tags		String
	Original window size in pixels		mm x mm
	Cropped	(y/n)	Selection, yes/no
	Pixel pitch		nm/pixel
	Magnification	magnification factor	Double
	Threshold	Threshold level for recognizing the melt pool boundary	Double
	Bit depth	the number of levels in grayscale or color scale	Integer
	Shutter Speed	the amount of time that the shutter is open for taking an image	s
	Optical filter bandwidth	minimum and maximum wavelengths	nm
	Sensor calibration information	The date of calibration, the method of calibration, person who performed the calibration, and the calibration data	String

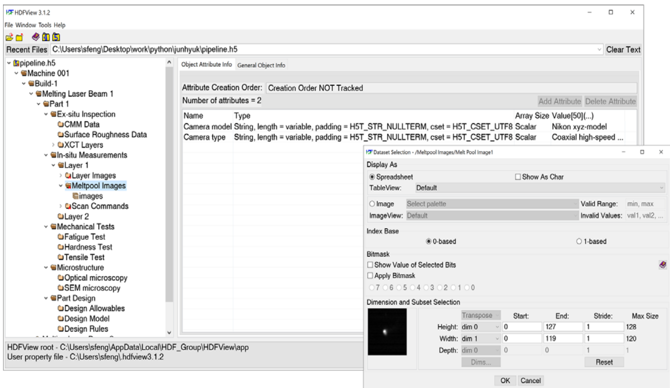

Fig. 3. Co-axial-image data structure.

3.8. Layer-wise images

Layer-wise images are taken from a staring camera. Required data elements are shown in Table 7. An example of layer-wise image taken from a staring camera can be found in Fig. 4. Both the image and its metadata are modeled in HDF5.

Table 7. Layer-wise image data elements.

Data element	Description		Data type
Image Name	the name of the image		String
Image ID	a unique identification (ID) number of the image		String
Time	the time it was taken		Date-time type
Layer ID	Identification of the layer (e.g., layer #)		String
Flash condition	if flash lights are used, a description of the flash light angle relative to the layer		String
Sensor ID	the identification of the image sensor		String
Sensor description	sensor type (e.g., InSb, CMOS, Photoiode), purchase data, wavelength ranges, lens distortion information, and other specifications, including filters.		String
Sensor configuration ID	Sensor configuration description must have the following tags		String
	Original window size in pixels		mm x mm
	Cropped	(y/n)	Selection, yes/no
	Pixel pitch		µm/pixel
	Magnification	magnification factor	Integer
	Viewing angle	(degree)	Double
	Bit depth	the number of levels on grayscale or color scale	Integer
	Shutter Speed	the amount of time that the shutter is open for taking an image	s
	Optical filter bandwidth	minimum and maximum wavelengths	nm
	Sensor calibration information	Calibration data, method, operator	String

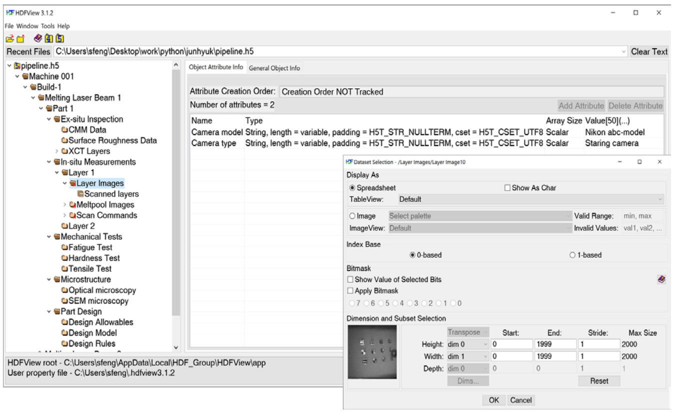

Fig. 4. Layer-wise-image data structure.

3.9. X-ray computed tomography

X-ray Computed Tomography (XCT) model is generated from a XCT scan of the fabricated part. An XCT model is a 3D model that can reveal defects inside a metal part. Required data elements are shown in Table 8. An example of an XCT images, which can be found in Fig. 5, is an image stack that is generated from a scan by an XCT instrument. Both the image and its metadata are placed in a file based on the HDF5 format.

Table 8. XCT model data elements.

Data element	Description	Data type
Source ID	the identification of the XCT source used with multiple	String

	sources	
Detector ID	the identification of the XCT detector in a multi-detector system	String
Scan ID	the identification of the scan	String
Model ID	The identification of the reconstructed model	String
Time and date	the date and time that the scan was completed	Date-time type
Sample temperature	temperature of sample in scanner	ºC
XCT Scanner geometric specification	a high-level indication of geometric conformance of generated as specified in ISO 10360:11	String
System calibration information	the date of calibration, artifact used, its date of last reference measurement	String
Geometric uncertainty estimate	estimate of measurement uncertainty, based on ISO 15530-3	
Detector data type (bit-depth)	the number of grayscale levels, e.g., uint16.	String
Compression information	description about compression applied in the file format	String
Volume height, width, and depth	shape of volume in numbers of pixels	
Axes order	row major or column major for 1-Dimensional data formats.	String
Voxel size	voxel dimension (mm) in the X, Y, and Z directions	
X-ray tube voltage		kV
X-ray tube current		µA
Target (anode) material	material type	String
Exposure (integration) time		s
Source to detector distance		mm
Source to the table Z-axis distance		mm
Physical filter	type and thickness of the filter	String

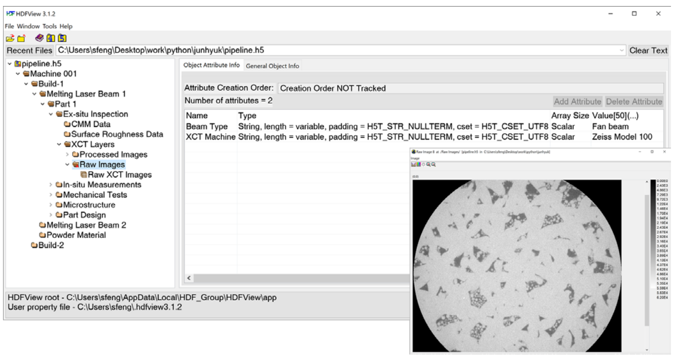

Fig. 5. XCT-image data structure.

3.10. Part model using a Coordinate Measuring Machine

The Part model can be generated using a Coordinate Measuring Machine (CMM). The model is computed from a point cloud generated by scanning a fabricated part using a CMM. It is commonly known as a CMM model, which is a 3D model that can represent the real part. Required data elements about CMM model are shown in Table 9.

Table 9. CMM model data elements.

Data element	Description	Data type
Machine ID	the identification of the CMM used	String
Uncertainty quantification	a high-level indication of measurement conforming to ISO 10360-2, 4, and 5.	String
Probe type	the types of CMM probes used in measurement	String
Model ID	the identification of the 3D CMM created	String
Setup	Part setup on the build platform in the melting laser beam coordinate system	String

3.11. Surface roughness

Surface roughness directly influences fatigue life, especially in medical devices. A measuring instrument is used to evaluate the 2D and 3D surface roughness. Required data elements are shown in Table 10.

Table 10. Surface roughness data elements.

Data element	Description	Data type
Instrument ID	the identification of the surface measurement instrument used	String
Type of surface roughness measurement	Linear measurement (e.g., Ra, Ry, Rz) or area measurement (e.g., Sa, Sy, Sz)	mm
Cutoff wavelength	The cutoff wavelength in surface roughness measurement	mm
Evaluation length/area	The length or area of the evaluation	mm or mm^2
Measuring speed		mm/s
Standard used	ISO, ASTM, etc.	String
Readout		µm

3.12. Microscopy

Optical and scanning electron microscopy (OM and SEM) are commonly used to characterize the microstructural features. To archive those images, required (meta-) data elements are highlighted in Table 11. An example of an optical microscopy image in HDF5 can be found in Fig. 6.

Table 11. Microstructural image (meta) data elements.

Data element	Description	Data type
Sample condition	description (e.g., etched)	String
Etch time	s	Date-time type
Image type	(e.g., tiff)	String
Magnification factor	(e.g., 50x)	Integer

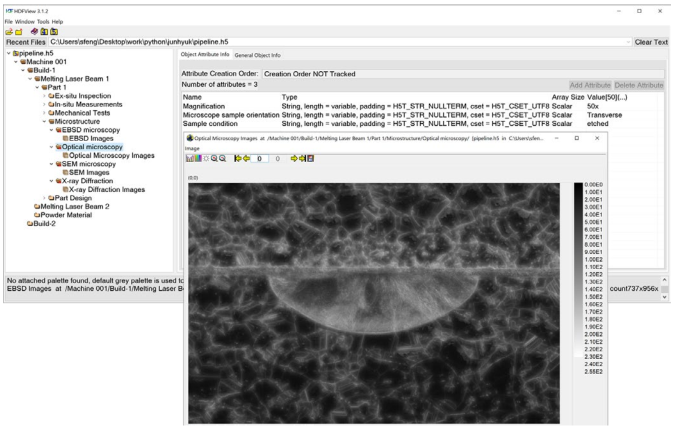

Fig. 6. Optical microscopy-image data structure.

3.13. *Electron backscattering diffraction SEM*

Electron Backscattering Diffraction (EBSD) SEM is commonly used for microstructural analysis with crystal orientations and morphology. To archive those EBSD SEM images, metadata elements are in Table 12. An example of an EBSD SEM image in HDF5 can be found in Fig. 7.

Table 12. EBSD SEM microstructural image (meta) data elements.

Data element	Description	Data type
Sample orientation	description (e.g., transvers, longitudinal to laser scanning direction)	String
Microscope sample orientation	description (e.g., front at the top of the sample mount)	String
Sample preparation	description	String
Magnification factor	(e.g., 50x)	Integer
Accelerating voltage		kV
Accelerating current		nA
Tilt angle		degree
Binning	e.g., 1 x 1	String
Scan area		µm x µm
Step size		µm
Image type	e.g., tiff	String
Comment	description	String

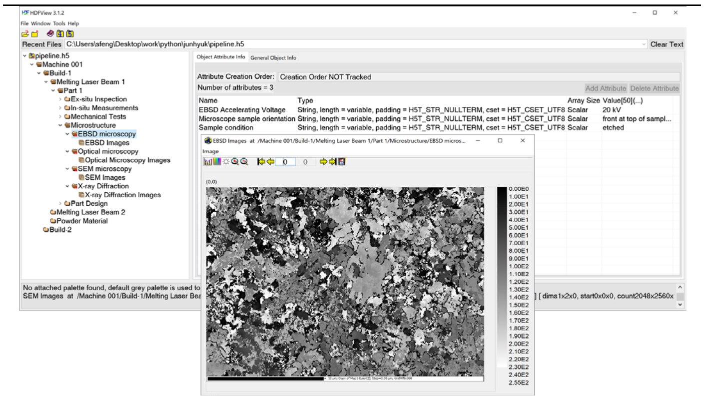

Fig. 7. EBSD SEM-image data structure.

3.14. *Powder X-ray diffraction*

Powder X-Ray Diffraction (PXRD) can be used for observing melt-pool depth and lattice structures of a grain. To archive PXRD images, metadata are listed in Table 13. An example of an PXRD image in HDF5 can be found in Fig. 8.

Table 13. PXRD image (meta) data elements.

Data element	Description	Data type
Diffractometer parameters	parameters used to specify the diffractometer	
Wavelength		Å
Measurement temperature		ºK
Start-2Θ	radian	radian
End-2Θ	radian	radian
Θ step size	radian	radian
Time per step		s
Gonio radius		mm

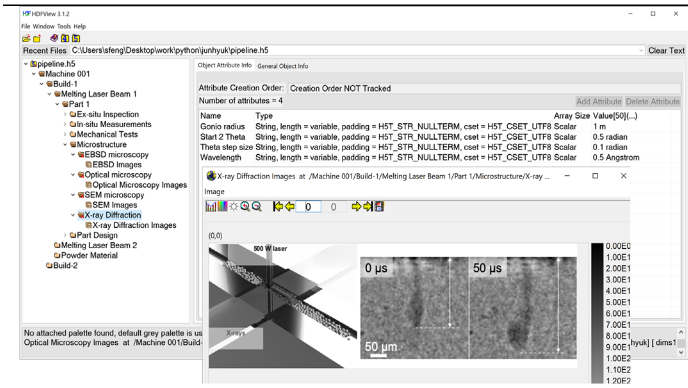

Fig. 8. Powder X-ray diffraction image data structure.

3.15. *Ultrasmall-angle X-ray spectroscopy*

Ultrasmall-Angle X-Ray Spectroscopy can be used to measure lattice structures and estimate residual stresses in the fabricated part. Small- and wide-angle X-Ray spectroscopy have the same metadata elements. To archive the images, those elements are in Table 14.

Table 14. Ultrasmall angle X-ray spectroscopy image (meta) data elements.

Data element	Description	Data type
Scattering type	ultrasmall, small, or wide angle	String
Sample orientation	description (e.g., transverse)	String
Beam line instrument	Description (e.g., ultrasmall angle X-Ray scattering instrument at beamline -ID-C)	String
Instrument notes	notes	String
Detector name	name	String
Detector type		String
Detector size		mm x mm
Wavelength		Å
Photon flux density		photons/s/mm^2
Horizontal slit description	text	String

Vertical slit description	Text	String
Acquisition time		s
Count time		s
Q-range	e.g., Qmin 0.0001 Qmax 0.3/ Å	/Å

3.16. Energy dispersive spectroscopy

Energy Dispersive Spectroscopy (EDS) can be used for analyzing elements in the fabricated part. To archive EDS images, required (meta) data elements are in Table 15. An example of an EDS image in HDF5 can be found in Fig. 9.

Table 15. Energy dispersive spectroscopy image (meta) data elements.

Data element	Description	Data type
Image width	(e.g., 12 µm)	µm
Image height	(e.g., 9 µm)	µm
EDS accelerating voltage		
Working distance	(e.g., 10 mm)	mm
Map file	(e.g., Mn Kalpha1)	String
Map image type	(e.g., tiff)	String
Detector size		mm x mm
Description	Text	String

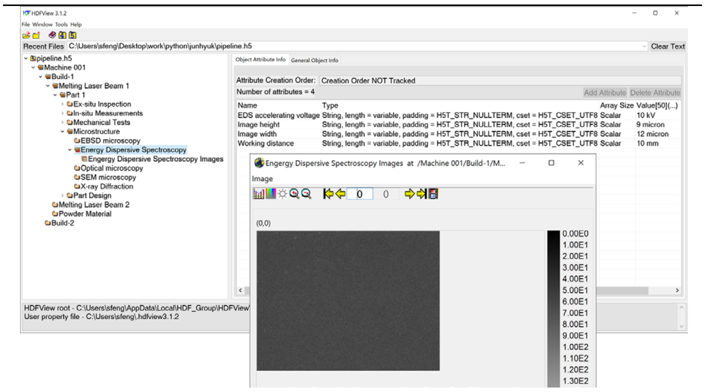

Fig. 9. EDS image data structure.

3.17. Mechanical property test

The sample mechanical property tests are demonstrated for tensile strength test, hardness test, and fatigue life test. To archive tensile strength test data, the meta-data are suggested in Table 16.

Table 16. Tensile test (meta) data elements.

Data element	Description	Data type
Tensile strength test machine ID		String
Machine model		String
Machine location		
Maximum load		
Coupon dimensions		
Coupon orientation	Relative to the build platform coordinate system	
Description		String
Yield stress		MPa
Ultimate tensile stress		MPa
Elongation		%

Hardness test data indicates how hard a fabricated coupon of a fabricated part is. To archive hardness test data, required (meta) data elements are in Table 17.

Table 17. Hardness test (meta) data elements.

Data element	Description	Data type
Hardness test machine ID		String
Machine model		String
Machine location		
Maximum load		
Coupon dimensions		
Coupon orientation	Relative to the build platform coordinate system	
Description		String
Indentation		String
Measured load		MPa
Type of hardness		String

Fatigue life test data indicates the number of cycles of a fabricated coupon. To archive fatigue-life, test data, required (meta) data elements are in Table 18.

Table 18. Fatigue life test (meta) data elements.

Data element	Description	Data type
Fatigue life test machine ID		String
Machine model		String
Machine location		
Maximum load		
Coupon dimensions		
Coupon orientation	Relative to the build platform coordinate system	
Description		String
Number of cycles that the part broke		Integer
Measured amplitude of the cyclical stress		MPa

4. Discussion

With advanced sensing technologies, massive datasets are generated from an AM build, including the machine, process plan, in-situ sensing, ex-situ inspection, microstructural analysis, and structural test. Part defects and out-of-tolerance features can be detected and analyzed using these datasets; the same datasets can be used for validation and qualification of PBF-LB/M AM parts and processes. A hierarchical data model is designed for these purposes. Such a model can contain many data groups, which explicitly (1) define the context for LPB-LB/M AM part fabrication and (2) enable the downstream data analytics for defect detection, process validation, and part qualification.

Hierarchical data structures are easy to understand and manipulate. For example, HDF5 images and their attributes can be stored in the same group (directory), which significantly helps users understand their contextual relations. AM data can be organized using HDF5 for different types of sensors used in different stage of a build - scan, melting, scanned layer, microstructure, and mechanical property. These data are properly organized to be consistent with different stages in AM part-fabrication. Application software can access these datasets for the subsequent data analytics for defect evaluation and creating a new control strategy.

HDF5 efficiently manages complex datatypes and datasets; however, it has limitations. HDF5 requires additional efforts to validate the data formats for data in schemas that are outside the ones modeled in HDF5. Since HDF5 compresses the dataset into a file, the ability for multiple users to access a file can be limited. Interestingly, data are never really deleted from the file; it is just disabled instead of removed. The file size can only be growing if not property managed.

The technology supporting new versions of HDF5 can be limited because new versions are developed by a volunteer community. To alleviate the potential problems, data developers can create a hierarchical data structure in a data server for easy update and parallel access by multiple users as a concept model.

5. Conclusions

The use of laser powder bed fusion, PBF-LB/M, processes to fabricate complex, AM metal parts in aerospace and medical industries has been increasing steadily. As a result, the demands on the quality and reliability of those parts have also increased. To respond to these demands, researchers and practitioners have started to use in-situ sensors and ex-situ measurement to detect potential anomalies in the parts. Organizing and archiving these related datasets are critical to process validation. Correlated datasets can also be used to verify the quality of AM parts. Organized data can be used as inputs to data analytics and other predictive tools.

In this paper, we described a data model with metadata elements in a hierarchical form to organize tables, text, and images for documenting machine, process, and part during an AM build. Images generated from in-situ monitoring sensors and ex-situ inspection instruments parts can be archived with text data, which generally include the attributes about the tables, images, signals, part design, material, and machine.

This model addresses the long-standing issue of how to organize textual descriptions, tables, images, and other types of data into a generic structure for the subsequent analyses. This model stores in-situ monitoring data, ex-situ monitoring data, coordinate measurements, microstructural analysis, AM machine status, and the part design model in a centrally managed file. The purpose is to share data with various applications. Examples in Section 3 show laser control commands, in-situ, and ex-situ images in HDF5 formats that can be used for such applications.

Future work will be in two areas. One is to validate this data model including time series data, such as acoustic signals and laser commands for infilling and contouring, mechanical property testing data, and other geometric data. Second is to develop a new, file management system including a procedure that will allow parallel/concurrent accessing of the data. In addition, we plan to use a part-development-lifecycle case study that includes design, build, processing plan, measurement, and test to show that well-organized data can enable qualification of AM parts.

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